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# THE IMPACT OF FISCAL INCENTIVES ON ELECTRIC VEHICLE ADOPTION IN EUROPE: A DYNAMIC APPROACH

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**Abstract**

Monetary incentives have been used worldwide to decrease high upfront costs of electric vehicles (EVs) and foster their adoption, but few empirical studies have analysed the effectiveness of such policies in Europe. The present thesis investigates the influence of consumer-side fiscal incentives on European EV adoption figures in 2010-2019 through a generalised method of moments (GMM) model. By exploiting the dynamic nature of the dependent variable, and controlling for socio-economic and attitudinal country-level data, I showed that the incentive design and the strength of network externalities in the country are critical determinants for the impact of monetary incentives.



Keywords: electric vehicles, consumer fiscal incentives, dynamic approach, Europe



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## 1. Introduction

The adoption of electric vehicles (EVs), as hybrid electric vehicles (HEVs), battery electric vehicles (BEVs) or plug-in-hybrid electric vehicles (PHEV), has in the past two decades been supported by public efforts from institutions over the globe. Despite their benefits in terms of fuel efficiency and lower emissions, electric vehicles still face adoption obstacles compared to standard internal combustion engine vehicles (ICEVs). On top of consumers concerns about driving range, vehicle reliability and disruptive technologies, widespread acceptance of EVs is hindered by their high upfront costs. Monetary incentives for consumers are hence seen as a critical determinant in reducing the reliance on fossil fuels of the transportation sector.

Average EV registrations in Europe increased from 44 in 2010 to 17,542 in 2019, while mean consumer incentives went from EUR 2,733 in 2010 to EUR 5,975 in 2019. However, few papers have focused on historical data to empirically study the European market, and almost none of them performed an analysis of EV adoption patterns through a dynamic approach. The present research investigates the impact of monetary incentives on EVs adoption rates in Europe through a generalised method of moments (GMM) model. The model results are refined by controlling for socio-economic conditions, concerns for the environment, and the presence of network effects (both through the public charging infrastructure channel and through other channels emerging from the natural growth of technology adoption). The results of the study aim to integrate and support past findings on consumer incentives design, the magnitude of their impact, and the conditions influencing their effectiveness, as well as to suggest a more comprehensive approach to the issue allowed by the use of a dynamic model.

This thesis is organised as follows: Section 2 provides an overview of the current literature on incentives efficiency in supporting electric vehicles; Section 3 outlines how the database was constructed; Section 4 serves as a preliminary analysis to ground the reasons for the database specification and methodology applied in the study (then presented in Section 5); and

Section 6 offers the main results of the study and compares them to the present literature. Finally, Section 7 concludes the study and outlines limitations and policy recommendations.

## 2. Literature review

Literature on the impact of incentives on EV adoption varies with respect to many dimensions. First, while most papers focus on (plug-in) hybrid electric vehicles, some more recent papers include battery electric vehicles too. Second, most analyses consider North American states or metropolitan cities, while seldom focus on cross-country analysis. Third, historical data studies differ in terms of methodology, with most papers relying on pooled ordinary least squares (OLS) or fixed-effects (FE) regressions. Finally, few studies specifically provide exact point estimates of the impact of incentives on vehicles adoption.

One of the first analyses, conducted by Diamond (2009), found only weak impact of public incentives on annual US-states sales of three HEV car models between 2001 and 2009, but a strong impact of gasoline prices. The author claimed this is due to car producers internalising the final price reductions in their pricing schemes - a hypothesis then rebutted by Salle (2011). The robust relationship between EV sales and fuel prices was confirmed in Chandra et al. (2010), who also concluded that tax rebates in Canadian provinces between 1989 and 2006 positively influenced HEV adoption. More specifically, HEV market share increased between 34% and 42% per USD 1,000 depending on the province and vehicle class analysed. Gallagher and Muehlegger (2011) used quarterly US-sales of HEV vehicles between 2001 and 2006 to show that the impact of incentives varied based on their type or, more precisely, on consumer time-discounting of incentive savings. Indeed, while sales tax reductions, age, and income had a positive effect on HEV registrations (which increased up to 45% following a sales tax waiver of USD 1,000), income tax credits were shown to have no statistical effect. DeShazo et al. (2014) analysed the impact of a Californian plug-in rebate program of around USD 1,838 per buyer and attribute to it 7% increase in BEV and PHEV market sales. Wee et al. (2018) used a dataset composed of bi-annual sales of EV vehicles in US states between 2010 and 2015, and found that a USD 1,000 increase in consumer subsidies led to a 5-10% increase in EV purchases, depending on the car model and state considered. Finally, Clinton and Steinberg (2019) took quarterly registration data of BEV in US states between 2011 and 2015 and applied to them different identification methods (FE regression and diff-in-diff with synthetic controls). The authors concluded that, while income tax credits had no impact on BEV registrations, a USD 1,000 increase in purchase rebates led to approximately 8% increase in registration figures. According to their analysis, direct financial incentives had a higher impact than charging stations availability, and private – not public – infrastructure positively correlated with BEV share (together with gender, education, and environmentalism). Other studies, not reported in depth for the sake of brevity, confirm the relationship between EV adoption and incentives (Beresteanu and Li 2011; Jin et al. 2014; Vergis and Chen 2014; Slowik and Lutsey 2017).

Outside North America, Sierzcula et al. (2014) analysed PEV market data from 30 countries in 2012 and found that consumer financial incentives and per-capita charging stations led to higher purchases, although the estimates are small. Hall and Lutsey (2017) used 2016 data from metropolitan areas in 14 countries and concluded that the availability of public charging stations and of consumer incentives were positively correlated with higher shares of adoption. Moreover, in most countries public charging stations supplemented – and did not replace – home and workplace charging. Similarly, Funke et al. (2019) reported an international comparison of literature on charging infrastructure. Since countries differ in terms of framework conditions (e.g. home ownership, share of detached houses and availability of home charging), there is no clear optimal amount of public stations. The authors concluded that a broad availability of home charging stations, and not necessarily of public infrastructure, is sufficient at early stages of electrification, and of primary importance for further developments in mature markets (e.g. Norway). A lower share of detached houses is generally correlated with a higher share of public charging infrastructure. Hence, public infrastructure is an important substitute to home charging primarily in countries with low home charging opportunities, like the Netherlands.

At the European level, most empirical studies consider Scandinavian countries, with few exceptions[1]. Aasness and Odeck (2015) focused on the Norwegian EV market between 2009 and 2015 and conducted a study on incentives in place. Tax, toll and parking fee exemptions, as well as access to high-occupancy vehicle (HOV) lanes, effectively nudged Norwegian consumers into buying electric vehicles. Langbroek et al. (2016) used a stated-choice experiment, rather than an econometric approach, to analyse the impact of policy incentives on Swedish consumers. By taking into account indirect network incentives to EV adoption (such as parking and charging discounts, or HOV lanes availability) on top of monetary incentives, they concluded that price-sensitivity of consumers decreased as they entered more advanced stages of EV acceptance. In line with the Transtheoretical Model of Change developed by Prochaska (1991), behavioural change is a process dependent on the learning curve, and not an event. Accordingly, people in more mature stages of behavioural change are already considering buying an EV, and thus are less responsive to subsidies. Plötz et al. (2016) was the first study that analyzed national European PEV sales data, and it concluded that income, fuel prices, and both direct and indirect incentives had an impact on PEV sales between 2010 and 2014. More specifically, a direct incentive of EUR 1,000 increased PEV sales share by about 16%. Sprei (2013; 2018) analysed the sales of flex-fuel vehicles (FFVs) in Sweden from 2002 to 2011, and focused, in particular, on the sharp drop in sales statistics after 2008. Their findings showed that lower gasoline prices and a change in the incentive policy after 2008 (from a point-

[1] Studies on Norway, especially, should be analysed with caution given the country's position as global leader in EV market share, with 46% of sales market share in 2018 (International Energy Agency 2019a).

of-sale rebate, to a smaller subsidy spread across the five years after purchase) were the most important determinants of the sales decrease. Finally, Münzel et al. (2019) used data similar to that of Plötz et al. (2016), but a more precise incentive modelling methodology, to analyse the impact of different incentives on 2010-2017 PHEV and BEV sales data. They find a 5-7% point estimate of incentives on EV share increase, which increases to 8% for rebates. They included a trend variable as an attempt to capture overall changes in technology diffusion, and found that it is significantly predicting future values of EV adoption rates.

On top of monetary incentives, the literature confirms the key role of environmental attitudes of consumers. Clinton and Steinberg (2019) used the share of Green-Party registered voters as a proxy for community environmentalism, while Gallagher and Muehlegger (2011) considered the per-capita Sierra Club membership rate. In their global analysis, Sierzcula et al. (2014) took into account the Environmental Performance Index from Yale University, and other studies (e.g. Li et al. 2017) included the share of commuters and the share of citizens that drive to work as proxies for environmental concern. In all previous cases, variables capturing environmentalism are positively correlated with EV adoption rate. Carley et al. (2013), Axsen et al. (2016), Nayum et al. (2016), and Priessner et al. (2018) built on the literature on cultural worldviews of Cherry et al. (2014) to analyse the attitudes of US, Canadian, Norwegian and Austrian representative EV buyers, respectively. The studies concluded that early EV buyers value low emissions and climate protection more than potential adopters or non-adopters, are more engaged in environment- and technology-oriented lifestyles, and concerned about dependency from foreign oil. For most studies, the inclusion of attitudinal variables reduces the predictive value of socio-economic factors. In other studies (e.g. Priessner et al. 2018) the former have an even stronger explanatory power than the latter.

Most studies make use of OLS and FE regressions or stepwise regressions, while only few papers consider the dynamics of the dependent variable, the policy feedback loops, and the possible endogeneity in OLS models by implementing Arellano and Bond estimators of GMM models. One of the first papers specifically accounting for network externalities is Jenn et al. (2013). This study analysed the increase in HEV vehicles in the US between 2000 and 2010, and modelled such increase by using the lagged dependent variable as an additional independent variable. Such methodology allowed to isolate the impact of exponential initial growth of EV technology and to avoid any overestimation of incentive effects. The studied policy, which provided income tax deductions of about USD 2,000 per buyer, was found to have increased HEV sales from 5% to 20%, depending on the car model considered. Such GMM estimates are however smaller than the estimates computed by the authors through a FE static model. Li et al. (2017) combined two theoretical models to study the effects of feedback loops on car purchases in 353 US metro-areas between 2010 and 2013. They estimated that income tax credit up to USD 7,500 had contributed to about 40% of EV sales, while network externalities through increases in charging stations amplified the policy shock, explaining 40% of that increase. Similarly, Springel (2017) studied the EV market in Norway between 2010 and 2015 and found a positive connection between car purchases and both consumer and charging station subsidies. Empirical data confirmed the positive relation between EV incentives and purchases, while a more structural approach corroborated the presence of network externalities of subsidies applied to both sides of the market. Jenn et al. (2018) studied PEV monthly registrations in the US between 2010 and 2015 and their relationship with individual tax credit and rebates. They found that applying a dynamic model reduces the estimates of rebates and other incentives compared to when using a static FE model. Overall, a USD 1,000 rebate leads to about 3% average increase in EV registrations, although different levels of consumer awareness on incentives can greatly increase the policy impact (up to 62% in California). The present analysis adds to this last group of studies using a dynamic methodology to assess the impact of public policy incentives and avoid possible overestimation.

## 3. Data structure

The thesis is based on the database used in Münzel et al. (2019) (hereafter, “the authors”), with some additions. The panel data spans between 2010 and 2019 and it comprises 31 countries: European Union countries (27), plus Island, Norway, Switzerland and the UK[2]. The dependent variable (*evshare*) is the share of the number of EV (BEV and PHEV) registrations (*evregs*) over the total number of vehicle registrations (*carregs*). The respective sources are the European Alternative Fuels Observatory (2020a) and Eurostat (2020a). Share variables, when used as dependent variables, should be logarithmically transformed to ensure normality of residuals, as advised by Wooldridge (2013). However, for observations with value of EV registrations equal to zero, the logarithm of the dependent variable is not defined. When the authors applied such transformation, then, they lost 30 observations out of the original 256, and ended up with an unbalanced dataset. On top of losing information, dropped observations are likely to be not randomly distributed[3]. Moreover, nine out of the dropped observations have non-zero values of fiscal incentives, i.e. the independent variable of interest. In order to circumvent these problems, I applied the following transformation to both the numerator of *evshare* (*evregs*) and its denominator (*carregs*). First, the following value $\varepsilon_i$ is calculated for each country:

$$\varepsilon_i = 0.001 * \max(evregs_{i,T}) \quad (1)$$

where *T* is the year that registered the highest value of *evregs* in country *i*. Secondly, $\varepsilon_i$ is added to all *evregs* and *carregs* values of country *i* across all the years of analysis. Lastly, the share of these two new variables is computed, which results in the *transformed evshare*[4]. No difference is introduced between the original and the transformed dependent variable for the same country

[2] Turkey has been excluded from the present analysis due to homogeneity reasons. Since the country never provided fiscal incentives throughout the period of analysis, its exclusion is not expected to change results dramatically.
[3] All of them belong to the 2010-2013 timespan, and mainly correspond to Eastern and Southern European countries.
[4] For instance, the maximum value of PEV registrations in Cyprus between 2010 and 2019 is 159. For all years, an epsilon equal to 0.159 is then added to *evregs* and *carregs*.

$i$ and year $t$, since both the transformed denominator and numerator are increased by the same amount. Moreover:

- As the following analysis takes into account within-country and not across-country variation, the transformation is not likely to bias results even though the added $\varepsilon_i$ changes from country to country.
- The largest within-country difference introduced is in the order of 1.11E-3 (corresponding to Iceland-2010)[5]. As such, the transformation introduced is considered to be small enough, even when accounting for the logarithmic form.
- A visual analysis of the *transformed evshare* confirms that largest *original-to-transformed evshare* differences correspond to observations in 2010 and 2011. These years also present values of monetary incentives which are mostly zero or small relative to the level of incentives in the following years.

Even with the transformation, then, estimates of the impact of fiscal incentives on EV registrations can be considered to be conservative. Such hypothesis is confirmed when confronting reduced database models present in Table 2 (based on the *transformed evshare*) with models in Appendix Table 1 (based on the *original evshare*). Overall, estimates based on the original dependent variable are inflated compared to those based on the transformed one, and this holds for all model specifications considered. The transformation is therefore effective in avoiding data loss, while at the same time it seems not to bias the estimates upwards.

The independent variable of interest is the volume of total incentives towards BEVs and PHEVs (*monetaryincenitve*). The final variable is given by the sum of six types of incentives: company car tax and circulation tax (i.e. recurring incentives); rebates, VAT deductions and other point-of-sale tax incentives (i.e. one-time incentives upon purchase of the vehicle); income tax deductions (i.e. one-time incentives after purchase of the vehicle). The calculation

[5] The second-larger one is in the order of 6.82E-4 (corresponding to Iceland-2011). For those two years, Iceland had no fiscal incentives, so one can assume the transformation does not influence the estimates of the monetary incentives.

of such incentives is based on yearly reports of the European Automobiles Manufacturers Association (ACEA 2010-2019) and follows the procedure outlined in Münzel et al. (2019). The procedure takes into account the average BEV and average PHEV tax payments vis-à-vis taxes corresponding to comparable ICEV models to compute the most accurate values of EV incentive savings (see Appendix A).

After adding socio-economic controls, I then expanded the original database from the authors by including attitudinal controls. The sources of database variables and their respective summary statistics are presented in Table 1 and in Appendix Table 2. In order to limit the number of variables introduced in the model, electricity price and diesel price are from now on combined into a single variable as the "ratio of electricity price over diesel price", i.e. the energy ratio (present in Table 1 only through its two components)[6]. Following the literature on the impact of environmental attitudes on EV adoption, I included two environmental variables: The Environmental Performance Index (EPI) from the Yale University Centre for Environmental Law & Policy (2010-2019), and the share of citizens that are pro-environmental incentives that is derived from the Eurobarometer Special surveys on "Attitudes of European Citizens Towards the Environment" (European Commission 2011, 2014, 2017, 2019a). The EPI provides yearly data on country-based ranking on environmental health and ecosystem vitality. It represents an overview of how close countries are to established environmental policy targets[7]. The second variable, instead, captures the share of citizens seeing fiscal incentives as an effective way to tackle environmental problems. The share of pro-incentive citizens reflects the percentage of respondents that agree that "Ensuring higher financial incentives (e.g., tax breaks, subsidies) to industry, business and citizens who protect the environment" is one of the most effective ways of tackling environmental problems. The variable presents three missing non-EU countries

[6] As the correlation between diesel and gasoline prices is high (above 0.80), diesel price only, and not gasoline price, is used to compute the energy ratio.

[7] As electric vehicles adoption is not directly included as composite of the index, possible simultaneity between the index and the dependent variable is excluded.

(Iceland, Norway and Switzerland), and is not continuous over the years of analysis[8]. Hence, the information provided on environmental attitudes is considered to be inferior when compared to that captured by the Environmental Performance Index.

**Table 1: List and sources of variables**

| Variable name | Variable code | Source | N |
|---|---|---|---|
| ***Share of EV registrations**** | evshare | European Alternative Fuels Observatory (2020); Eurostat (2020a) | 310 |
| ***Monetary incentive*** | monetaryincentive | European Automobiles Manufacturers Association (2010-2019) | 310 |
| ***Demographics:*** | | | |
| - Population | population | Eurostat (2020b) | 310 |
| - Population density | density | World Bank (2020) | 310 |
| ***Automotive industry:*** | | | |
| - Public charging stations* | charging | European Alternative Fuel Observatory (2020b) | 310 |
| - Car stock | carstock | Eurostat (2020c) | 310 |
| - Total km of motorways | km | Eurostat (2020d) | 310 |
| - Electricity price | electrcityprice | Eurostat (2020e) | 310 |
| - Diesel price* | dieselperliter | European Commission (2019b) | 310 |
| - Gasoline price* | gasperliter | European Commission (2019b) | 310 |
| - Oil Imports | oilimports | Eurostat (2020f) | 310 |
| ***Socio-economic:*** | | | |
| - Net income median | netincomemedian | Eurostat (2020g) | 310 |
| - Unemployment rate | unemployment | Eurostat (2020h) | 310 |
| - Gini index | gini | Eurostat (2020i) | 310 |
| - Income 80-20 ratio* | income8020ratio | Eurostat (2020j) | 310 |
| - Home-ownership rate | homeownershiprate | Eurostat (2020k) | 310 |
| - Share of houses* | dwellingtypehouse | Eurostat (2020l) | 310 |
| - Education* | education | Eurostat (2020m) | 310 |
| ***Attitudinal:*** | | | |
| - Environmental Performance Index | epi | Yale University Centre for Environmental Law & Policy (2010-2019) | 310 |
| - Share of pro-incentive citizens | env_incentives | Eurobarometer (EC 2011; EC 2014; EC 2017; EC 2019) | 276 |

* Notes: The share of EV registrations refers to the *transformed* dependent variable. As diesel and gasoline price are highly correlated, only the former is used to contruct the energy ratio. Total public charging stations is given by the sum of "fast charging stations" and "slow charging stations". The income 80-20 ratio compares how much richer the top 20% of households are compared to the bottom 20%. Share of houses represents the share of dwellings that are houses, or similar types of buildings. Education captures the share of people between 25 and 64 years old with tertiary education.

To sum up, the database used in this thesis is based on the one provided by Münzel et al., (2019), with the following changes. First, the period of analysis was expanded to include 2018 and 2019. Second, Turkey has been excluded for homogeneity and data availability reasons. Third, the dependent variable is now transformed, as outlined above, and balanced. Fourth, the database includes two variables controlling for environmental attitudes. Finally, the variable for monetary incentives in Estonia now includes positive incentives between 2012 and 2014. According to different sources (European Environment Agency 2016; International Energy Agency 2019b; Gerdes 2013), the Estonian government offered rebates equivalent to half of

[8] Moreover, pre-EU values for Croatia are missing, since the country entered the Union in 2014 only.

the price of the vehicle (up to EUR 18,000) between 2012 and 2014. These rebates were overlooked by the authors. Appendix Figure 1 presents the evolution of monetary incentives and EV shares in Estonia. The dependent variable, indeed, displays a spike in the years corresponding to the policy.

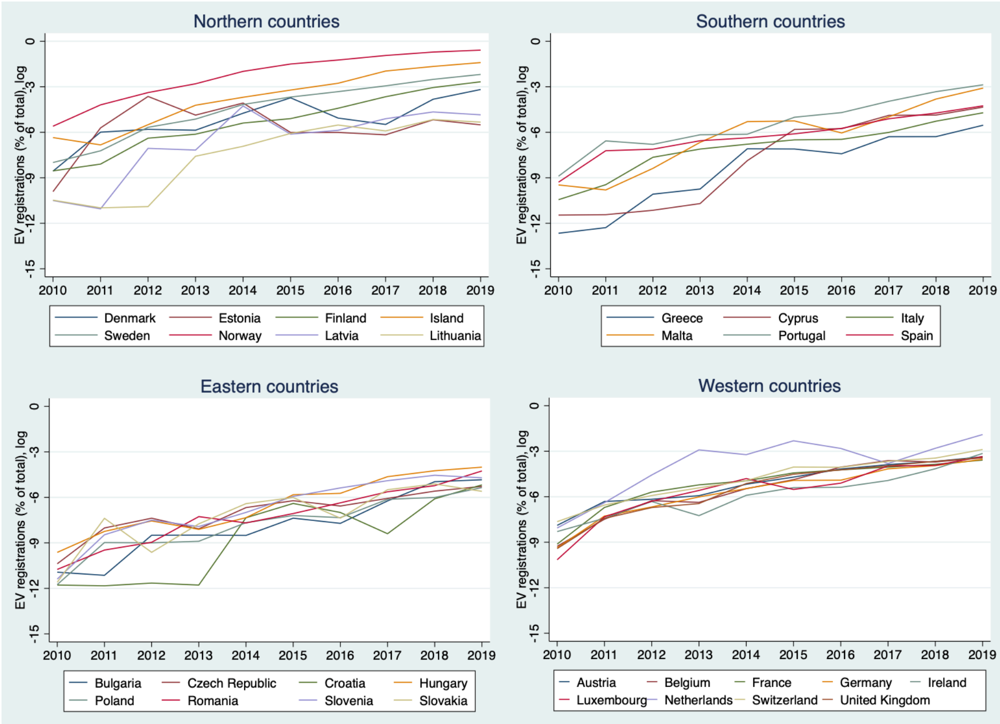
## 4. Preliminary analyses: FE model and database considerations

A graphical analysis of Figure 1 suggests the presence of a positive trend pattern in the dependent variable. Moreover, when performing a simple OLS regression of the share of electric vehicle on only a time trend variable, in 30 out of 31 countries the trend variable is statistically significant[9]. Estonia is the only country where the trend is not significant, as also suggested by Appendix Figure 1. With respect to the monetary incentive variable, values of incentives are generally higher for Northern countries, but the variable does not display a clear upward trend (Appendix Figure 2). As expected, both monetary incentives and public charging stations are positively correlated with the share of EV adoption (the correlation coefficients are 0.49 and 0.39, respectively)[10].

As part of a preliminary analysis, I tested the presence of policy selection on the level of incentives. Endogenous policy application might make it difficult to interpret results, as values of monetary incentives might be affected by the dependent variable. A probit model (with a dummy for the presence of monetary incentives as dependent variable) and a FE model (with the continuous variable of monetary incentives as dependent variable) are presented in Appendix Table 3. Particular attention needs to be taken when modelling the share of EV in such models. Fiscal policies are usually discussed months before implementation and enter in force from the year following the policy debate. Hence, in presence of policy selection based

[9] Following Münzel et al. (2019), the trend variable is given by the natural logarithmic form of each year. For instance, for values in year 2010 the variable trend takes a value of "ln(2010)".
[10] The two independent variables are also positively correlated with each other (correlation coefficient of 0.25).

**Figure 1: Share of electric vehicles (BEV and PHEV) registrations by region (log)**




on EV share levels, one would expect EV registrations *of the previous year* to have an impact on the decision of policymakers to introduce incentives from the following year on. Hence, I included a one-period lagged value of EV share as independent variable in the regressions. The results show that the only significant variable in the models is the number of charging stations (both lagged one year and not). Other lagged variables have been included but are not significant. Overall, then, there is no evidence of this type of endogeneity.

As mentioned in the previous section, Münzel et al. (2019) move from a balanced database to an unbalanced (hereafter, "reduced") dataset when they apply the logarithmic transformation to the dependent variable. The transformation, however, is likely to change the database non-randomly. To understand what characteristics are decisive in defining which countries have a zero value of EV registrations, I run a probit model on a dummy variable with value of 1 when the country exhibits positive values of EV share, and 0 otherwise (see Appendix Table 4). As expected, monetary incentives predict the presence of electric vehicle registrations[11]. Moreover,

[11] Charging stations are omitted from the regression because positive values of the variable predict success perfectly.

observations with zero EV registrations differ in six other characteristics from observations with positive values of the dependent variable: unemployment, education, car stock, population density, km of motorways and environmental performance. This confirms that the exclusion of observations with zero registrations is not random, and that the use of a transformed dependent variable to avoid information loss is justified.

To further understand how a different transformation of the dependent variable implies different results, I replicated what was previously done by the authors. Changes in my model, compared to what was done by the authors, include the addition of the charging stations variable and the transformed dependent variable (see Section 3 for a more complete list of changes in the database). In line with Münzel et al. (2019), the country fixed-effects model includes a trend variable, the monetary incentive variable, and the energy ratio. To this base model, I then add the lagged variable of charging stations stock as further control. As done by Clinton and Steinberg (2019), such variable needs to be included in order to reduce possible omitted variable bias, but it needs to be lagged to avoid the introduction of simultaneity. While it is less likely to introduce simultaneity in the model through the variable capturing fiscal incentives (since the level of incentives is decided *in the previous years*), current increases in the demand for charging stations might be the result of *current increases* in EV registrations. This type of simultaneity might affect the consistency of estimates. A modified Wald statistic for groupwise heteroskedasticity test and a Jochmans Portmanteau test for within-group correlation exhibit signs of heteroskedasticity and first order within-groups serial correlation. Standard errors are hence clustered at the country level. The model is then applied on different database specifications and with the exclusion or inclusion of public charging stations.

Table 2 confirms that monetary incentive estimates are sensitive to the database considered. However, with or without the inclusion of charging stations, and with or without the inclusion of Estonia, estimates of the monetary incentive variable are higher when the reduced database

**Table 2: Country fixed-effects models**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Without public charging stations | | | | With charging stations | | | |
| | Full database | | Reduced database | | Full database | | Reduced database | |
| | All | Without Estonia | All | Without Estonia | All | Without Estonia | All | Without Estonia |
| VARIABLES | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare |
| monetaryincentive | 0.093* | 0.044 | 0.104** | 0.061** | 0.126** | 0.073** | 0.127** | 0.079** |
| | (0.050) | (0.030) | (0.046) | (0.028) | (0.053) | (0.035) | (0.048) | (0.030) |
| log_elecdieselratio | -0.934 | -0.816 | -0.640 | -0.510 | -0.225 | -0.128 | -0.004 | 0.115 |
| | (0.744) | (0.737) | (0.432) | (0.415) | (0.890) | (0.887) | (0.472) | (0.452) |
| L.charging | | | | | -0.062*** | -0.065*** | -0.038*** | -0.041*** |
| | | | | | (0.013) | (0.012) | (0.012) | (0.010) |
| Trend | 1,162.348*** | 1,215.502*** | 981.645*** | 1,039.135*** | 1,068.934*** | 1,136.968*** | 902.924*** | 967.434*** |
| | (71.414) | (56.910) | (66.966) | (42.014) | (105.215) | (92.149) | (70.782) | (46.461) |
| Constant | -8,851.726*** | -9,255.657*** | -7,476.109*** | -7,913.036*** | -8,139.521*** | -8,656.688*** | -6,875.893*** | -7,366.224*** |
| | (543.505) | (433.554) | (509.201) | (319.752) | (801.262) | (702.260) | (538.320) | (353.703) |
| Observations | 310 | 300 | 284 | 275 | 279 | 270 | 267 | 258 |
| R-squared | 0.818 | 0.841 | 0.828 | 0.858 | 0.780 | 0.812 | 0.816 | 0.855 |
| Number of countryid | 31 | 30 | 31 | 30 | 31 | 30 | 31 | 30 |
| Adjusted R-squared | 0.852 | 0.852 | 0.852 | 0.852 | 0.852 | 0.852 | 0.852 | 0.852 |

Reduced databases include only observations for which the value of PEV registrations is positive.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

is considered. Moreover, the presence of a year trend in the dependent variable pattern is confirmed. While the results for monetary incentive and for the energy ratio are in line with what is expected from the literature, the direction and significance of the lagged charging stations variable is surprising. Although it is not clear why this is the case, the analysis in Appendix B on the impact of charging stations on the dependent variable provides evidence that the time specifications under the static FE model (i.e. through the use of a year trend variable or of year dummies) might not be the optimal model choice for this relationship.

The preliminary analysis confirmed the absence of policy selection between the dependent variable and the monetary incentive variable. Moreover, database specifications are shown to greatly change incentive coefficients. With the use of an unbalanced dataset and a linear model, it is difficult to isolate the true historical impact of incentives. Indeed, the estimation of incentive coefficients needs to be purged from two biases:

- *The bias stemming from positive network externalities.* In the absence of a model that accounts for the time persistency of EV registrations (i.e. the "natural growth" of the technology adoption curve and the network externalities besides public charging stations), the estimates of monetary incentives might be inflated.

- *The bias stemming from underlying country characteristics.* The unbalanced database might mask differences in countries that adopted electric vehicles earlier or later on in the decade. Such differences might then wrongly be attributed to the level of incentives available, rather than to other country characteristics.

By using a balanced dataset, which *by definition* gives the same weight to all countries, the impact of the second bias is reduced, and the impact of incentives can be better isolated. Further, a dynamic model takes into account the impact of network externalities on levels of EV registrations by allowing for the baseline level of registrations (from which following adoption rate growth occurs) to change over time. Additionally, this methodology copes with possible endogeneity between the dependent variable and the charging infrastructure, as well as ultimately avoids the overestimation of incentive coefficients.

## 5. Final Methodology: GMM on Balanced Dataset

According to Roodman (2009), a GMM dynamic model can be applied if: (1) the process of the dependent variable is dynamic, with current levels influenced by past levels; (2) some regressors, such as public charging stations, might be endogenous or predetermined, meaning that current disturbances are influenced by past values; (3) the panel is short; (4) the idiosyncratic disturbances suffer from heteroskedasticity and serial correlation; (5) such disturbances are uncorrelated across individuals. While the previous section gave evidence of the possible predetermined nature of the charging stations variable, the present and following sections further support the hypothesis of the dynamic nature of the dependent variable. Out of the remaining conditions to use GMM models[12], the last assumption is the one that requires more caution, and it is more likely to be satisfied if time-varying factors are included as regressors.

[12] The short panel structure (i.e. N>T) has been discussed in section 3, and evidence of heteroskedasticity and serial correlation has been found when studying the FE model in Section 4.

As outlined in Bond (2002), pooled OLS estimates of a model including the lagged dependent variable present an upward bias, while within-group FE estimates present a downward bias in short panels (Nickell, 1981). Hence, pooled OLS and FE models are expected to provide the upper and lower bound estimates for GMM consistent estimators. If difference-GMM estimators are close to FE estimators, one has evidence of Nickell bias and weak instrumentation being present. System-GMM should in that case be preferred[13]. Since difference-GMM estimates for the dependent variable have a coefficient around 0.38 and thus similar to the one provided by the FE model (see Appendix Table 5), system-GMM models are to be preferred in this case. Moreover, the significance of the lagged dependent variable confirms the dynamic time structure of the data, which was instead modelled through a FE regression with year trend by Münzel et al. (2019). The general GMM model takes the following form:

$$\begin{aligned}\log(share\ of\ EV\ registrations)_{it} = {} & \delta_{it-1}\log(share\ of\ EV\ registrations)_{it-1} + \beta_1 monetary\ incentive_{it} \\ & + \beta_2 \log(energy\ ratio)_{it} + \beta_3 charging_{it} + \beta_4 controls_{it} + \delta_t + \varepsilon_{it}\end{aligned} \quad (2)$$

where $t$ is the year and $i$ is the country considered. The model uses as internal instruments the 1-4 lags of the monetary incentive and energy ratio variables, and the 2-4 lags of the dependent and charging stations variables[14]. As the validity of instruments in system GMM depends on the assumption that they are uncorrelated with unobserved country-fixed effects, the use of time controls (and their inclusion as external instruments) is highly recommended (Roodman 2009). However, when running the GMM models with time trend and performing a Pesaran CD test, the hypothesis of cross-section independence, essential for consistent GMM estimates, is not satisfied. The hypothesis is instead confirmed when including year dummies in the model ($\delta_t$), and also as external instruments. Indeed, as dummies are assumed to be orthogonal to country-fixed effects, their inclusion ensures that the fifth assumption described above is satisfied.

[13] Moreover, system-GMM is suggested if T is short and the dependent variable is persistent (Blundell and Bond, 1998).

[14] The first lags of the dependent variable and of charging stations are not included as instruments due to the dynamic nature of the former and the predetermined nature of the latter.

As suggested by Roodman (2009), all controls entering the basic model are included as instruments as well, and instruments are collapsed to avoid overidentification. In models with additional controls, such variables are also included as instruments only conditional on models not suffering from weak instrumentations given by too many instruments. Moreover, as the data presents panel groupwise heteroskedasticity, standard errors are clustered at the country level. In presence of heteroskedasticity the Sargan test is unreliable, hence only p-values of the Hansen test are reported in the following section. Finally, a Ramsey RESET test for misspecification of the linear model is performed and the hypothesis of misspecification is rejected. The current model is correctly specified as linear.

With few exceptions, models in the next section are trustworthy. In the Arellano-Bond tests for AR(1), the null-hypothesis of no first-order serial correlation is rejected. Moreover, in the AR(2) tests, the null-hypothesis of no second-order correlation in disturbances is never rejected. In all models, the number of instruments is lower than the number of groups, and the p-values of the Hansen tests are well above 0.10 but not suspiciously high[15]. Overall, the dynamic models are correctly capturing the persistency in EV registrations (i.e. the lagged dependent variable is always statistically significant) and the values of the lagged dependent variable lie within the expected upper and lower bounds presented in Appendix Table 5.

## 6. Results and sensitivity analyses

Table 3 reports results for GMM estimates of monetary incentives across different specifications. Overall, Model 4 is chosen for its completeness in control variables, number of observations, and values on the post-estimation tests (Arellano-Bond and Hansen tests). The other models in Table 3 are to be interpreted as sensitivity analyses to better study monetary incentive estimates, and are sorted in this manner for the sake of consistency with Table 2[16].

[15] High p-values in the Hansen test could instead be a sign of overidentification and weak instrumentation (Roodman 2009).
[16] The considerations done in the present section also hold when analysing models excluding Estonia (Appendix Table 6).

**Table 3: Basic GMM regressions**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Baseline | Baseline and epi | Charging stations | Charging stations and epi | Charging and incentives approval | Components of charging stations | Components of charging stations and epi |
| VARIABLES | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare |
| L.log_evshare | 0.587*** | 0.581*** | 0.607*** | 0.603*** | 0.472*** | 0.575*** | 0.580*** |
| | (0.161) | (0.151) | (0.150) | (0.137) | (0.121) | (0.138) | (0.131) |
| monetaryincentive | 0.089** | 0.092** | 0.097* | 0.095* | 0.095* | 0.094* | 0.095* |
| | (0.042) | (0.040) | (0.056) | (0.052) | (0.055) | (0.050) | (0.052) |
| log_elecdieselratio | -0.183 | -0.203 | -0.284 | -0.278 | -1.097 | -0.160 | -0.243 |
| | (0.939) | (0.942) | (0.791) | (0.727) | (1.124) | (1.045) | (0.975) |
| charging | | | 0.000 | 0.001 | 0.009 | | |
| | | | (0.010) | (0.013) | (0.018) | | |
| fastchargers | | | | | | -0.000 | -0.000 |
| | | | | | | (0.000) | (0.000) |
| slowchargers | | | | | | 0.000 | 0.000 |
| | | | | | | (0.000) | (0.000) |
| epi | | -0.021 | | -0.014 | | | -0.006 |
| | | (0.043) | | (0.045) | | | (0.043) |
| env_incentives | | | | | -0.076 | | |
| | | | | | (0.066) | | |
| Constant | -3.185 | -1.170 | 0.000 | 0.000 | -3.965 | -3.294 | 0.000 |
| | (2.597) | (4.624) | (0.000) | (0.000) | (3.896) | (2.580) | (0.000) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 279 | 279 | 279 | 279 | 249 | 279 | 279 |
| Number of countryid | 31 | 31 | 31 | 31 | 28 | 31 | 31 |
| Number of Instruments | 21 | 21 | 24 | 24 | 25 | 24 | 24 |
| AR(1) | 0.013 | 0.010 | 0.010 | 0.007 | 0.008 | 0.010 | 0.008 |
| AR(2) | 0.350 | 0.331 | 0.339 | 0.330 | 0.390 | 0.330 | 0.328 |
| Hansen | 0.148 | 0.152 | 0.217 | 0.251 | 0.471 | 0.286 | 0.247 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In all models, estimates of the lagged dependent variable are highly significant, and incentive estimates for the respective models are lower than under the FE specifications in Table 2 (in line with Jenn et al. 2013, Li et al. 2017, Jenn et al. 2018). Compared to Table 2, where the inclusion of the charging stations variable greatly increases incentives estimates (from 9.3% to 12.6%), GMM estimates after the inclusion of charging stations vary less (from 8.9% to 9.7%). Although never significant, charging stations estimates are positive in the GMM regressions (differently from FE models). The inclusion of the EPI variable in the baseline GMM model increases the estimates (Table 3, Column 1 vis-a-vis Column 2), possibly due to a reduction in omitted variable bias. However, such addition decreases the estimates compared to the charging stations model (Table 3, Column 3 vis-a-vis Column 4), as previously found in the literature (e.g. Clinton and Steinberg 2019). The inclusion of the share of pro-incentive citizens variable in Model 5 leads to similar estimates. Models 6 and 7 including the components of charging station infrastructure, i.e. fast and slow public chargers, suggest similar incentive coefficients than the ones found in models with the total level of charging stations. Moreover, Model 4 estimates are also consistent to the inclusion of socio-economic variables (see Appendix Table 7), with estimates ranging from 7.7% to 12.2%. Overall, a EUR 1,000 increase in monetary incentives accounted on average for about 8-9% increase in European 2010-2019 EV registration shares.

The impact of monetary incentives can be split into one-time and recurring incentives. In line with previous literature (Gallagher and Muehlegger 2011, Sprei 2018, Münzel et al. 2019, Clinton and Steinberg 2019), Appendix Table 8 confirms that the most salient incentives are the ones which most affect consumer choices, i.e. one-time purchase incentives (and, more specifically, incentives at purchase), rather than future income tax or recurrent incentives. When further splitting the purchase incentive variable in its most basic elements (Table 4), rebates is the only component which is statistically significant. The model in Column 1 of Table 4 needs to be taken with caution, since the high p-value of the Hansen test could be a sign of weak instrumentation. Instead, Models 2-4 confirm the consumer-discounting hypothesis first theorised by Gallagher and Muehlegger (2011): rebates, being the most immediate, direct and salient out of all fiscal policies, are the incentives that most impact consumer choices. Moreover, rebate estimates of 9.1% and their level of significance are similar to what was found in the models of Table 3 considering the full monetary incentive variable. Finally, public charging stations are shown to have a slightly positive impact on EV shares.

To better analyse the relationship between feedback loops and incentives, I sectioned the database by lower and upper halves of EV registration shares[17]. In the following GMM models, the level of EV registration shares is to be interpreted as a proxy for the natural growth in the technology adoption and for the feedback loops in terms of all other positive network externali-

[17] The bottom section also contains the 28 observations with zero EV registrations. The mean value of positive EV shares used as a threshold is 0.019, dividing the sections into 132 and 145 observations respectively.

**Table 4: Components of purchase incentives**

| VARIABLES | (1)<br>Components of purchase incentives<br>log_evshare | (2)<br>Rebate<br>log_evshare | (3)<br>Point-of -purchase taxes<br>log_evshare | (4)<br>Vat deductions<br>log_evshare |
|---|---|---|---|---|
| L.log_evshare | 0.521*** | 0.570*** | 0.651*** | 0.653*** |
| | (0.141) | (0.121) | (0.080) | (0.095) |
| - Purchase incentives | | | | |
| - Rebates | 0.169** | 0.091** | | |
| | (0.082) | (0.044) | | |
| - Point-of-purchase taxes | 0.164 | | 0.122 | |
| | (0.185) | | (0.082) | |
| - VAT deductions | -0.268 | | | 0.094 |
| | (0.181) | | | (0.104) |
| log_elecdieselratio | -1.659 | -0.905 | -0.187 | -0.060 |
| | (1.764) | (0.832) | (1.311) | (1.335) |
| charging | 0.004 | 0.025* | 0.014 | 0.025** |
| | (0.026) | (0.013) | (0.016) | (0.011) |
| epi | -0.024 | -0.042 | -0.029 | -0.030 |
| | (0.018) | (0.026) | (0.023) | (0.030) |
| Constant | 0.000 | 0.000 | 0.074 | 0.000 |
| | (0.000) | (0.000) | (3.709) | (0.000) |
| Time dummies | Yes | Yes | Yes | Yes |
| Observations | 279 | 279 | 279 | 279 |
| Number of countryid | 31 | 31 | 31 | 31 |
| Number of Instruments | 28 | 26 | 26 | 26 |
| AR(1) | 0.020 | 0.009 | 0.006 | 0.007 |
| AR(2) | 0.449 | 0.342 | 0.300 | 0.319 |
| Hansen | 0.702 | 0.328 | 0.394 | 0.293 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

ties that lie outside the channel of public charging infrastructure (that the model actively takes into account) - e.g. behavioural acceptance of EV cars, increased availability and saliency of new EV car models, indirect incentives such as HOV lanes. The upper half of the database contains observations in countries and years where network externalities are assumed to be stronger. A first analysis of the two different sections is provided in Table 5. Column 1 presents results for the lower section, i.e. for observations with lower network externalities, and has indeed a lower estimate for the lagged value of the dependent variable compared to the upper section columns. Column 2 displays results for the upper section model, which, apart from presenting higher persistency in the lagged dependent variable, shows signs of possible second-order correlation due to the higher persistency of the dependent variable (p-value of 0.106 for

AR(2)). Since this could lead to inconsistent estimates, a model including also a two-period lagged dependent variable is run. The resulting model (Column 3) presents improved p-values of the Arellano-Bond and Hansen tests.

**Table 5: Interaction between network externalities and incentives, by data sectioning**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Lower section | Upper section | | Lower section | Upper section |
| VARIABLES | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare |
| L.log_evshare | 0.554** | 0.802*** | 0.881*** | 0.552** | 0.713*** |
| | (0.226) | (0.181) | (0.098) | (0.200) | (0.161) |
| L2.log_evshare | | | 0.050 | | 0.050 |
| | | | (0.130) | | (0.135) |
| monetaryincentive | 0.079* | 0.129* | 0.072** | 0.115* | 0.103** |
| | (0.042) | (0.074) | (0.032) | (0.060) | (0.039) |
| log_elecdieselratio | -0.279 | -0.138 | 0.261 | 0.017 | -0.073 |
| | (1.473) | (1.041) | (1.358) | (1.044) | (1.364) |
| charging | -0.160 | -0.011 | -0.013 | -0.151 | -0.007 |
| | (0.102) | (0.015) | (0.010) | (0.239) | (0.013) |
| epi | 0.075* | -0.021 | -0.001 | 0.035 | -0.013 |
| | (0.039) | (0.034) | (0.032) | (0.053) | (0.048) |
| unemployment | | | | -0.125* | -0.139 |
| | | | | (0.068) | (0.101) |
| Constant | 0.000 | -0.371 | 1.104 | 0.000 | 0.000 |
| | (0.000) | (3.018) | (5.475) | (0.000) | (0.000) |
| Time dummies | Yes | Yes | Yes | Yes | Yes |
| Observations | 132 | 147 | 145 | 132 | 145 |
| Number of countryid | 30 | 31 | 31 | 30 | 31 |
| Number of Instruments | 26 | 27 | 27 | 26 | 28 |
| AR(1) | 0.071 | 0.053 | 0.022 | 0.044 | 0.081 |
| AR(2) | 0.848 | 0.106 | 0.159 | 0.337 | 0.197 |
| Hansen | 0.355 | 0.109 | 0.184 | 0.324 | 0.286 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Although the number of observations in the upper and bottom section is similar, further caution needs to be taken to exclude the possibility of introducing selection bias when sectioning the database. Recalling what was discussed in Section 4, observations with positive EV registrations differ from those with zero EV registrations with respect to at least seven variables. Caution needs now to be taken to ensure that observations in the highest and lowest halves of EV shares do not statistically correspond to countries with different characteristics. To avoid that eventuality, a probit model is run (Appendix Table 9). The dependent variable is 0 for observations with values lower than the mean value of EV share (0.019 threshold), and 1 for the observations above the threshold. The results suggest that observations differ only in terms of the unemployment level and, as expected, by the incentives amount. Therefore, in order to avoid selection bias and have reliable estimates, the previous models on upper and lower sections of Columns 1 and 3 are run again after controlling for the level of unemployment.

Even when controlling for this possible cause of selection bias, monetary incentive estimates are significant at both levels of network externalities. Although in all models incentive estimates are positive and significant, when analysing the upper section the estimates slightly decrease (Table 5 Column 1 vis-a-vis Column 3; Column 4 vis-a-vis Column 5). The incentive coefficients are lower when network externalities are established and stronger, possibly due to the fact that the price-sensitivity of consumers decreases as markets advance in the process of behavioural change (Langbroek et al. 2016). While for the lower section in Column 1 environmental attitudes positively predict EV adoption rates, when controlling for the unemployment level in Model 4 such impact loses its significance, supporting the hypothesis that socio-economic conditions are critical at first stages of electrification. In turn, a higher unemployment level is associated with lower EV registration shares for observations where network externalities - other than public charging infrastructures - are weaker.

Results by monetary incentive composition in Appendix Table 10 are in line with what was discussed until now. Indeed, rebates are the only type of incentives for which estimates are consistently positive and significant, and estimates of incentives decrease with higher levels of network externalities. A similar analysis between upper and lower levels of feedback loops is performed by sectioning years in the database before and after 2014 (see Appendix Table 11). As suggested also in Jenn et al. (2013), both the natural growth of EV technology adoption and indirect positive network externalities are assumed to progressively increase as time passes. Again, results show higher values of monetary incentive estimates in the first years of analysis.

## 7. Discussion and conclusion

Most empirical studies on the fiscal incentives towards EV adoption focus on the identification of policies to which consumers react the most, and on the description of what are the characteristics of the marginal consumer reactive to such policies. This research combined the analysis of past EV registration patterns with European socio-economic and attitudinal country-level data, while controlling for network externalities (in terms of public charging infrastructure or not) and the natural growth of the EV technology through the use of a dynamic model. The identification of such model has been a central piece of the study. Departing from the data structure of Münzel et al. (2019), this research applied a transformation to the dependent variable EV share and added attitudinal controls and public charging infrastructure to the model of the authors. Compared to Münzel et al. (2019), the impact of incentives is here decoupled from the bias coming from using an unbalanced dataset. Additionally, compared to previous studies at the European level, the influence of fiscal policies is also purged from the upwards bias in FE estimates stemming from not accounting for positive network externalities.

The present study revealed that, when using a FE static model, incentive estimates are more subject to changes in the database and are not correctly accounting for the natural growth in technology adoption. Instead, by exploiting the dynamic nature of the dependent variable, GMM models presented in this research provide more stable and smaller point estimates, since they allow to better account for the possible endogeneity in predetermined regressors (e.g. charging stations) and for the natural growth in the technology adoption curve. Overall, and in line with previous studies (Jenn et al. 2013, Plötz et al. 2016, Wee et al. 2018, Clinton and Steinberg 2019), a EUR 1,000 increase in consumer fiscal incentives accounted on average for about 8-9% increase in European 2010-2019 EV market share in terms of car registrations.

This research found that concern for environmental protection from policymakers and society is significant in predicting initial levels of EV registrations, but its impact is less critical than that of socio-economic factors, such as the level of unemployment. Secondly, public charging infrastructure is not consistently linked to higher EV registrations. In line with previous literature (Hall and Lutsey 2017, Clinton and Steinberg 2019, Funke et al. 2019), it might be the case that private infrastructure, but not necessarily public charging, is associated with higher rates of adoption. Unfortunately, such data are unavailable in the database constructed. The lack of information on private charging stations, on local or regional incentives, and on more indirect incentives apart from public charging infrastructure (HOV lane accessibility, home-charging subsidies, parking fee exemptions etc.) are some of the limitations of the present study. Even more decisive to provide further insights on the patterns of EV adoption would be a higher data granularity, in terms of more years of analysis, regional distinction between urban and rural sales, and the availability of EV sales data by vehicle model.

Network infrastructures besides public charging stations are significant in determining successive EV adoption rates and have a slightly offsetting effect on the impact of monetary incentives, as also illustrated by Langbroek et al. (2016). Indeed, when a country already presents above-average levels of EV registrations, the impact of monetary incentives is less critical to increasing EV adoption even further, ceteris paribus. Policymakers are then suggested to first understand where national consumers stand in the process of EV adoption, and only then adapt the magnitude and type of the monetary incentive policy to be introduced. Additionally, incentive design is significant in predicting policy effectiveness in shaping consumer decisions (as previously presented by Gallagher and Muehlegger 2011, Sprei 2018, Münzel et al. 2019, Clinton and Steinberg 2019). Fiscal incentives, especially in their most salient and direct form of rebates, are critical at initial stages of EV transition and maintain a positive influence on registrations even at further stages of electrification. Empirically, rebates are proven to be the EV fiscal policy to which consumers have reacted the most, and thus represent the incentive design that most certainly boosts the process of transition to electrical mobility.

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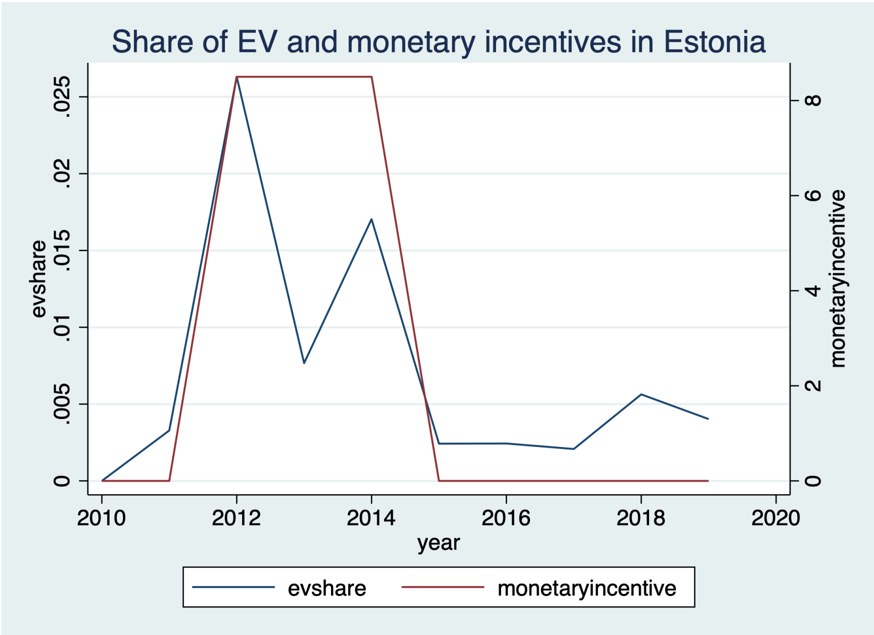
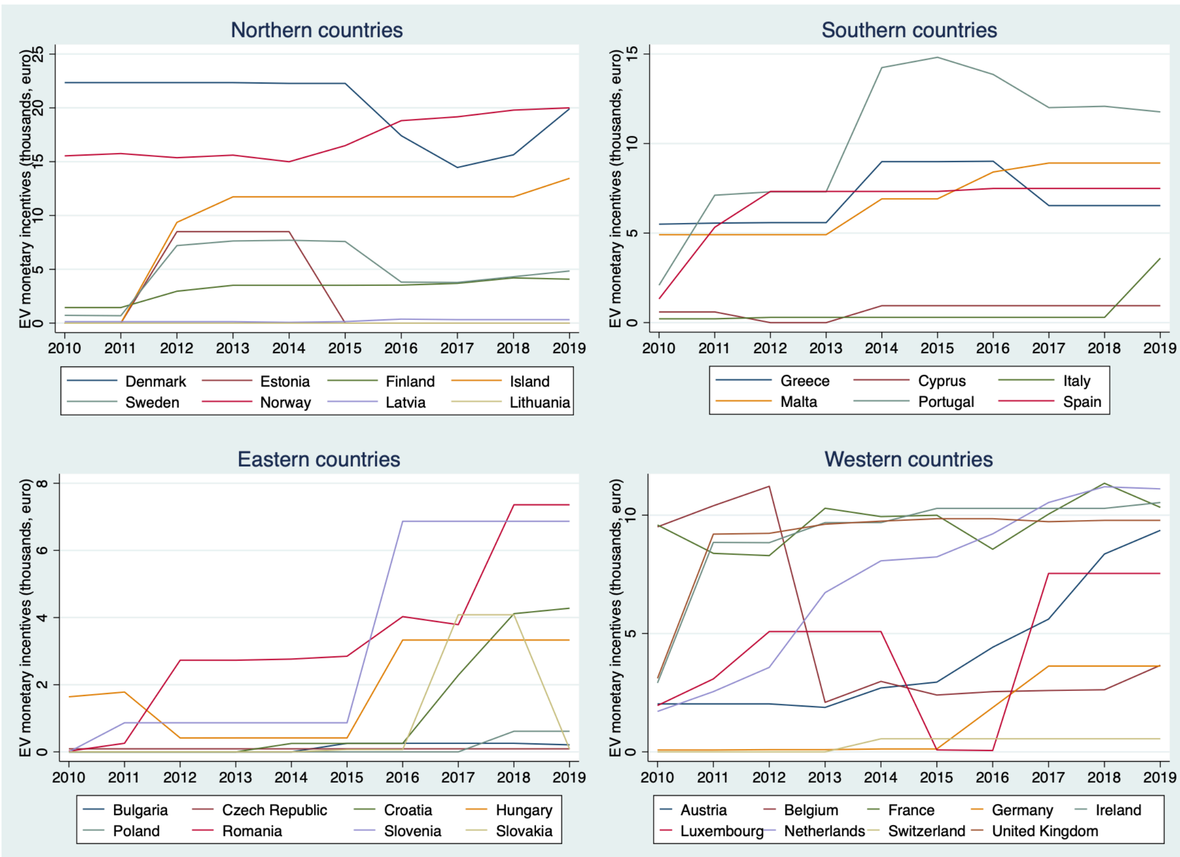
## Appendix

### Appendix Figure 1: Share of EV and monetary incentives in Estonia




### Appendix Figure 2: Monetary incentives by region (thousands, Euro)



## Appendix Table 1: Fixed-effects model using the original dependent variable

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Without public charging stations | | With charging stations | |
| | All | Without Estonia | All | Without Estonia |
| VARIABLES | log_original_evshare | log_original_evshare | log_original_evshare | log_original_evshare |
| monetaryincentive | 0.122** | 0.081** | 0.140*** | 0.094** |
| | (0.048) | (0.034) | (0.049) | (0.035) |
| log_elecdieselratio | -0.767 | -0.636 | 0.003 | 0.126 |
| | (0.457) | (0.443) | (0.498) | (0.479) |
| L.charging | | | -0.043*** | -0.046*** |
| | | | (0.012) | (0.011) |
| Trend | 1,023.444*** | 1,079.838*** | 926.409*** | 989.912*** |
| | (70.119) | (47.373) | (72.256) | (49.297) |
| Constant | -7,794.533*** | -8,223.128*** | -7,054.651*** | -7,537.322*** |
| | (533.235) | (360.531) | (549.570) | (375.310) |
| Observations | 284 | 275 | 267 | 258 |
| R-squared | 0.821 | 0.847 | 0.814 | 0.850 |
| Number of countryid | 31 | 30 | 31 | 30 |
| Adjusted R-squared | 0.847 | 0.847 | 0.847 | 0.847 |

Note: The model analysed are to be considered as "reduced database" only, since for models based on the original evshare the distinction between "reduced database" and "full database" becomes trival. Indeed, by using the original evshare as dependent variable one is, by construction, dropping observations for which the dependent variable is zero. Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

## Appendix Table 2: Summary statistics

| Variable | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| log_evshare | 310 | -6,08 | 2,37 | -12,66 | -0,58 |
| monetaryincentive | 310 | 4,85 | 5,39 | 0,00 | 22,35 |
| population | 310 | 16,83 | 2,23 | 0,32 | 83,78 |
| density | 310 | 168,87 | 247,66 | 3,17 | 1.514,47 |
| charging | 310 | 2,46 | 6,37 | 0,00 | 50,59 |
| km | 310 | 264,50 | 371,56 | 11,50 | 1.552,30 |
| electricityprice | 310 | 17,48 | 5,04 | 8,22 | 31,25 |
| dieselperliter | 310 | 1,30 | 0,17 | 0,92 | 1,81 |
| gasperliter | 310 | 1,38 | 0,18 | 0,98 | 2,02 |
| oilimports | 310 | 30,22 | 39,69 | 0,67 | 154,27 |
| netincomemedian | 310 | 16,44 | 10,48 | 2,02 | 44,13 |
| unemployment | 310 | 8,67 | 4,79 | 2,00 | 27,50 |
| gini | 310 | 29,61 | 4,47 | 20,90 | 43,50 |
| income8020ratio | 310 | 4,80 | 1,15 | 3,03 | 9,93 |
| dwellingtypehouse | 310 | 58,88 | 15,98 | 33,10 | 95,60 |
| homeownershiprate | 310 | 74,39 | 11,65 | 41,30 | 97,60 |
| education | 310 | 31,61 | 8,66 | 11,90 | 47,30 |
| epi | 310 | 73,71 | 8,86 | 44,80 | 93,48 |
| env_incentives | 276 | 30,08 | 9,53 | 14,00 | 57,00 |

Note: The total number of observations is given by 31 countries and 10 years of analysis, although for the variable on the share of pro-incentive citizens is not balanced. As the dependent variable is a share between 0 and 1, its logarithmic value is negative. All variables are expressed in thousands to ease the interpretation of graphs and estimates.

## Appendix Table 3: Testing the presence of policy selection

| VARIABLES | (1)<br>Probit model<br>Dummy for<br>monetaryincentive | (2)<br>FE model<br>Amount of<br>monetaryincentive |
|---|---|---|
| L.log_evshare | 1.410 | 0.334 |
| | (4.806) | (0.234) |
| charging | 3.918 | 0.078** |
| | (14.263) | (0.032) |
| log_electricityprice | -0.277 | -0.111 |
| | (1.384) | (0.119) |
| dieselperliter | -3.908 | 1.112 |
| | (8.664) | (1.156) |
| netincomemedian | -0.235 | 0.010 |
| | (1.656) | (0.181) |
| unemployment | -0.081 | 0.005 |
| | (0.472) | (0.072) |
| homeownershiprate | -0.272 | 0.095 |
| | (1.168) | (0.173) |
| education | 0.089 | 0.117 |
| | (1.102) | (0.133) |
| density | 0.016 | 0.006 |
| | (0.171) | (0.006) |
| km | 0.069 | -0.005 |
| | (0.361) | (0.012) |
| epi | -0.132 | -0.024 |
| | (0.227) | (0.032) |
| Constant | 51.819 | -1.516 |
| | (137.155) | (16.142) |
| Observations | 279 | 279 |
| Number of countryid | 31 | 31 |
| Log-likelihood | -39.75 | |
| R-squared | | 0.198 |
| Adjusted R-squared | | 0.165 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Appendix Table 4: Do values of zero in EV registrations depend on country characteristics?

| VARIABLES | Probit<br>Dummy for presence<br>of EV registrations |
|---|---|
| monetaryincentive | 0.291*** |
| | (0.092) |
| log_elecdieselratio | -0.667 |
| | (0.885) |
| netincomemedian | -0.048 |
| | (0.039) |
| unemployment | -0.156*** |
| | (0.042) |
| education | 0.057** |
| | (0.026) |
| homeownershiprate | -0.006 |
| | (0.025) |
| dwellingtypehouse | 0.004 |
| | (0.010) |
| carstock | 0.000* |
| | (0.000) |
| density | -0.001** |
| | (0.001) |
| km | 0.003* |
| | (0.002) |
| epi | 0.067** |
| | (0.031) |
| Constant | -4.882 |
| | (3.648) |
| Observations | 310 |
| Number of countryid | 31 |
| Log-likelihood | -488.220 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Appendix Table 5: Upper and lower bonds of lagged dependent variable estimates

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Baseline | | Charging stations and epi | | Charging stations, epi and unemployment | |
| | Pooled OLS | Fixed Effects | Pooled OLS | Fixed Effects | Pooled OLS | Fixed Effects |
| VARIABLES | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare |
| L.log_evshare | 0.782*** | 0.326*** | 0.757*** | 0.303*** | 0.692*** | 0.305*** |
| | (0.043) | (0.089) | (0.049) | (0.092) | (0.056) | (0.096) |
| monetaryincentive | 0.039*** | 0.082** | 0.039*** | 0.095*** | 0.046*** | 0.095** |
| | (0.013) | (0.036) | (0.012) | (0.034) | (0.014) | (0.035) |
| log_elecdieselratio | -0.044 | -0.611 | -0.103 | -0.547 | -0.027 | -0.546 |
| | (0.209) | (1.071) | (0.222) | (1.071) | (0.239) | (1.044) |
| charging | | | 0.004 | -0.032*** | 0.004 | -0.034*** |
| | | | (0.005) | (0.009) | (0.005) | (0.010) |
| epi | | | 0.012 | -0.014 | 0.014 | -0.014 |
| | | | (0.010) | (0.014) | (0.010) | (0.014) |
| unemployment | | | | | -0.037** | 0.015 |
| | | | | | (0.013) | (0.045) |
| Constant | -0.903 | -6.647*** | -2.077 | -5.841** | -2.360* | -5.916** |
| | (0.657) | (2.027) | (1.262) | (2.342) | (1.215) | (2.328) |
| Observations | 279 | 279 | 279 | 279 | 279 | 279 |
| R-squared | 0.862 | 0.812 | 0.863 | 0.820 | 0.868 | 0.820 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Appendix Table 6: Basic GMM regressions with the exclusion of Estonia

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Baseline | Baseline and epi | Charging stations | Charging stations and epi | Charging and incentives approval | Components of charging stations | Components of charging stations and epi |
| VARIABLES | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare |
| L.log_evshare | 0.588*** | 0.575*** | 0.606*** | 0.603*** | 0.424*** | 0.589*** | 0.672*** |
| | (0.178) | (0.175) | (0.149) | (0.137) | (0.136) | (0.140) | (0.113) |
| monetaryincentive | 0.085* | 0.088** | 0.087* | 0.095* | 0.089 | 0.087* | 0.075** |
| | (0.046) | (0.041) | (0.048) | (0.052) | (0.055) | (0.046) | (0.031) |
| log_elecdieselratio | -0.077 | -0.033 | -0.195 | -0.278 | -0.825 | 0.003 | -0.500 |
| | (0.930) | (0.933) | (0.661) | (0.727) | (1.380) | (1.158) | (0.686) |
| charging | | | 0.002 | 0.001 | 0.015 | | |
| | | | (0.009) | (0.013) | (0.017) | | |
| fastchargers | | | | | | -0.000 | -0.000 |
| | | | | | | (0.000) | (0.000) |
| slowchargers | | | | | | 0.000 | 0.000 |
| | | | | | | (0.000) | (0.000) |
| epi | | -0.031 | | -0.014 | | | -0.009 |
| | | (0.045) | | (0.045) | | | (0.032) |
| env_incentives | | | | | -0.043 | | |
| | | | | | (0.063) | | |
| Constant | 0.000 | 0.045 | 0.000 | 0.000 | 0.000 | 0.000 | -2.470 |
| | (0.000) | (4.703) | (0.000) | (0.000) | (0.000) | (0.000) | (3.438) |
| Observations | 270 | 270 | 270 | 279 | 240 | 279 | 270 |
| Number of countryid | 30 | 30 | 30 | 31 | 27 | 31 | 30 |
| Number of Instruments | 21 | 21 | 24 | 24 | 25 | 25 | 30 |
| AR(1) | 0.022 | 0.020 | 0.015 | 0.014 | 0.020 | 0.010 | 0.010 |
| AR(2) | 0.513 | 0.478 | 0.502 | 0.478 | 0.533 | 0.336 | 0.481 |
| Hansen | 0.206 | 0.205 | 0.395 | 0.326 | 0.633 | 0.373 | 0.629 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Appendix Table 7: GMM Model 4 regressions with socio-economic controls**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Gini | Income 80-20 ratio | Unemployment | Median net income | Education | Share of dwelling houses | Population density | Population | Car stock |
| VARIABLES | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare |
| L.log_evshare | 0.595*** | 0.629*** | 0.549*** | 0.580*** | 0.552*** | 0.537*** | 0.646*** | 0.510*** | 0.520*** |
| | (0.164) | (0.147) | (0.160) | (0.146) | (0.154) | (0.134) | (0.132) | (0.116) | (0.123) |
| monetaryincentive | 0.087* | 0.077* | 0.122* | 0.085* | 0.112* | 0.079* | 0.089* | 0.103** | 0.100* |
| | (0.047) | (0.040) | (0.061) | (0.045) | (0.062) | (0.045) | (0.048) | (0.048) | (0.050) |
| log_elecdieselratio | -0.538 | -0.360 | -0.018 | -0.439 | -0.257 | -0.525 | -0.860 | -1.067 | -0.319 |
| | (0.681) | (0.697) | (0.632) | (0.982) | (0.964) | (1.272) | (0.666) | (1.458) | (1.053) |
| charging | 0.003 | 0.002 | -0.003 | -0.004 | -0.010 | 0.003 | 0.002 | -0.026 | -0.029 |
| | (0.015) | (0.014) | (0.013) | (0.012) | (0.018) | (0.017) | (0.011) | (0.017) | (0.019) |
| epi | 0.002 | 0.004 | -0.002 | -0.032 | 0.011 | -0.033 | 0.001 | -0.014 | 0.007 |
| | (0.048) | (0.046) | (0.034) | (0.063) | (0.034) | (0.027) | (0.032) | (0.040) | (0.033) |
| gini | 0.069 | | | | | | | | |
| | (0.058) | | | | | | | | |
| income8020ratio | | 0.113 | | | | | | | |
| | | (0.218) | | | | | | | |
| unemployment | | | -0.034 | | | | | | |
| | | | (0.044) | | | | | | |
| netincomemedian | | | | 0.032 | | | | | |
| | | | | (0.030) | | | | | |
| education | | | | | 0.029 | | | | |
| | | | | | (0.061) | | | | |
| dwellingtypehouse | | | | | | 0.025 | | | |
| | | | | | | (0.042) | | | |
| density | | | | | | | -0.000 | | |
| | | | | | | | (0.000) | | |
| population | | | | | | | | 0.025 | |
| | | | | | | | | (0.024) | |
| carstock | | | | | | | | | 0.000 |
| | | | | | | | | | (0.000) |
| Constant | -6.004 | -3.829 | -2.797 | -1.117 | -5.174 | -3.579 | -3.636 | -4.202 | -4.128 |
| | (4.563) | (4.717) | (3.211) | (6.240) | (3.840) | (4.631) | (3.309) | (3.111) | (3.518) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 279 | 279 | 279 | 279 | 279 | 279 | 279 | 279 | 279 |
| Number of countryid | 31 | 31 | 31 | 31 | 31 | 31 | 31 | 31 | 31 |
| Number of Instruments | 28 | 28 | 27 | 27 | 28 | 28 | 28 | 28 | 28 |
| AR(1) | 0.014 | 0.010 | 0.013 | 0.009 | 0.015 | 0.012 | 0.006 | 0.009 | 0.011 |
| AR(2) | 0.353 | 0.369 | 0.335 | 0.338 | 0.390 | 0.338 | 0.341 | 0.360 | 0.391 |
| Hansen | 0.284 | 0.304 | 0.300 | 0.243 | 0.450 | 0.439 | 0.244 | 0.431 | 0.341 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

## Appendix Table 8: One-time incentives vs recurring incentives

| | (1) | (2) |
|---|---|---|
| | One-time vs recurring incentives | Components of one-time incentives |
| VARIABLES | log_evshare | log_evshare |
| L.log_evshare | 0.553*** | 0.516*** |
| | (0.123) | (0.174) |
| Recurring incentives | 0.033 | 0.457 |
| | (1.158) | (1.485) |
| One-time incentives | 0.106** | |
| | (0.040) | |
| - Income tax incentives | | 0.176 |
| | | (0.638) |
| - Purchase incentives | | 0.105* |
| | | (0.058) |
| log_elecdieselratio | -0.408 | -0.311 |
| | (1.163) | (1.609) |
| charging | 0.011 | 0.000 |
| | (0.027) | (0.032) |
| epi | -0.029 | -0.027 |
| | (0.022) | (0.020) |
| Constant | -2.057 | 0.000 |
| | (3.267) | (0.000) |
| Time dummies | Yes | Yes |
| Observations | 279 | 279 |
| Number of countryid | 31 | 31 |
| Number of Instruments | 28 | 28 |
| AR(1) | 0.011 | 0.020 |
| AR(2) | 0.315 | 0.337 |
| Hansen | 0.360 | 0.199 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Appendix Table 9: Do higher values in EV registrations depend on country characteristics?**

| VARIABLES | (1)<br>Probit<br>Probability of being in the upper section |
|---|---|
| monetaryincentive | 0.177** |
| | (0.076) |
| log_elecdieselratio | 0.221 |
| | (0.887) |
| netincomemedian | 0.018 |
| | (0.054) |
| unemployment | -0.338*** |
| | (0.098) |
| education | 0.218 |
| | (0.159) |
| homeownershiprate | 0.084 |
| | (0.067) |
| dwellingtypehouse | -0.052 |
| | (0.041) |
| carstock | 0.000 |
| | (0.000) |
| density | 0.000 |
| | (0.001) |
| km | 0.001 |
| | (0.002) |
| epi | 0.019 |
| | (0.022) |
| Constant | -10.127 |
| | (8.239) |
| Observations | 310 |
| Number of countryid | 31 |
| Log-likelihood | -113.15 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Appendix Table 10: Interaction between network externalities and incentive components, by data sectioning

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | One-time vs recurring incentives | | Components of one-time incentives | | Components of purchase incentives | |
| | Lower section | Upper section | Lower section | Upper section | Lower section | Upper section |
| VARIABLES | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare | log_evshare |
| L.log_evshare | 0.492** | 0.754*** | 0.434** | 0.758*** | 0.541** | 0.758*** |
| | (0.185) | (0.139) | (0.210) | (0.157) | (0.218) | (0.187) |
| L2.log_evshare | | -0.006 | | 0.001 | | 0.012 |
| | | (0.140) | | (0.130) | | (0.131) |
| Recurring incentives | 0.150 | 0.115 | 0.165 | 0.072 | | |
| | (0.196) | (0.309) | (0.253) | (0.364) | | |
| One-time incentives | 0.113** | 0.085* | | | | |
| | (0.052) | (0.044) | | | | |
| - Income tax incentives | | | -0.008 | 0.348 | | |
| | | | (0.248) | (0.316) | | |
| - Purchase incentives | | | 0.130* | 0.082* | | |
| | | | (0.067) | (0.048) | | |
| - Rebates | | | | | 0.193** | 0.124** |
| | | | | | (0.092) | (0.055) |
| - Point-of-purchase taxes | | | | | 0.169* | 0.080 |
| | | | | | (0.098) | (0.061) |
| - VAT deductions | | | | | -0.220** | 0.058 |
| | | | | | (0.080) | (0.073) |
| log_elecdieselratio | 0.042 | -0.027 | 0.112 | -0.241 | 0.633 | -0.314 |
| | (0.908) | (0.795) | (1.537) | (0.856) | (1.240) | (0.502) |
| charging | -0.037 | -0.008 | -0.033 | -0.008 | -0.202 | -0.010 |
| | (0.148) | (0.013) | (0.254) | (0.015) | (0.307) | (0.012) |
| epi | 0.034 | 0.015 | 0.046 | 0.008 | 0.047 | 0.027 |
| | (0.057) | (0.040) | (0.041) | (0.039) | (0.069) | (0.031) |
| unemployment | -0.122* | -0.106 | -0.094 | -0.131 | -0.061 | -0.073 |
| | (0.064) | (0.091) | (0.077) | (0.098) | (0.072) | (0.087) |
| Constant | 0.000 | 0.000 | 0.000 | 0.000 | -4.132 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (6.703) | (0.000) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 132 | 145 | 132 | 145 | 132 | 145 |
| Number of countryid | 30 | 31 | 30 | 31 | 30 | 31 |
| Number of Instruments | 27 | 29 | 27 | 29 | 28 | 29 |
| AR(1) | 0.050 | 0.058 | 0.077 | 0.066 | 0.041 | 0.077 |
| AR(2) | 0.336 | 0.200 | 0.489 | 0.171 | 0.611 | 0.131 |
| Hansen | 0.391 | 0.257 | 0.330 | 0.274 | 0.135 | 0.296 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Appendix Table 11: Interaction between network externalities and incentives, by years of analysis**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | All | | Without Estonia | |
| | 2010-2014 | 2015-2019 | 2010-2014 | 2015-2019 |
| VARIABLES | log_evshare | log_evshare | log_evshare | log_evshare |
| L.log_evshare | 0.508*** | 0.445*** | 0.557*** | 0.478*** |
| | (0.156) | (0.113) | (0.179) | (0.104) |
| monetaryincentive | 0.129** | 0.095** | 0.125* | 0.102** |
| | (0.060) | (0.042) | (0.069) | (0.042) |
| log_elecdieselratio | -1.134 | -0.451 | -0.846 | -0.112 |
| | (1.140) | (0.860) | (1.251) | (0.587) |
| charging | 0.071 | 0.019 | 0.056 | 0.008 |
| | (0.071) | (0.019) | (0.059) | (0.011) |
| epi | -0.038 | -0.049 | -0.055 | -0.018 |
| | (0.032) | (0.066) | (0.040) | (0.057) |
| Constant | -2.677 | -0.760 | 0.000 | -2.148 |
| | (3.786) | (4.908) | (0.000) | (4.784) |
| Time dummies | Yes | Yes | Yes | Yes |
| Observations | 124 | 155 | 120 | 150 |
| Number of countryid | 31 | 31 | 30 | 30 |
| Number of Instruments | 20 | 22 | 20 | 22 |
| AR(1) | 0.024 | 0.010 | 0.026 | 0.007 |
| AR(2) | 0.215 | 0.760 | 0.172 | 0.261 |
| Hansen | 0.280 | 0.816 | 0.260 | 0.848 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Appendix A: Modelling of the variable on monetary incentives

The procedure to derive the variable *monetaryincentive* follows five steps, as outlined in Münzel et al. (2019).

First of all, the market share of BEV and PHEV models throughout the period of analysis is considered. Between 2010 and 2019, the most sold BEV model was Nissan Leaf (154,675 units)[18], while the most sold PHEV model was Mitsubishi Outlander PHEV (158,330 units) (European Commission 2018; Cars Sales Base 2019). The prices and car specifications of these two car models are used as benchmarks for BEV and PHEV cars, respectively. Secondly, the two models are paired with two comparable internal combustion engine vehicles (ICEVs) in terms of price, characteristics and market share: VW Golf and VW Tiguan. Thirdly, European Commission Car Price Indexes between 2005 and 2011 (EC 2005; EC 2006; EC 2007; EC 2008; EC 2009; EC 2010; EC 2011) are used as benchmarks to compute country-based mean car price indexes for VW Golf. Using German car models mean prices between 2010 and 2019 as numeraire, and the computed mean VW Golf country price indexes, country-mean prices by model are determined. Four mean prices, one for each model, are then computed for each country. Fourthly, taxes and incentives given in ACEA Tax Reports are derived for the corresponding four types of models, and the average incentives by electric vehicle model are computed: taxes corresponding to the registration of a Nissan Leaf are compared to taxes corresponding to the registration of a VW Golf, resulting in the *BEV mean incentive*; the same is done between Mitsubishi Outlander PHEV and VW Tiguan, resulting in the *PHEV mean incentive*. Lastly, the two mean incentives (BEV and PHEV) are averaged to yield the final average incentive for EV registration.

[18] Although the most sold BEV car in the period analyzed was actually the Renault Zoe (173,250 units), its availability began in 2013 only. For the sake of consistency in price availability, then, Nissan Leaf is used as benchmark BEV model, since its commercialization started in 2010.

This fourth step is repeated for each of the six components of monetary incentives: rebates, point-of-sale taxes, VAT deduction (i.e. purchase incentives); income tax deductions (i.e. one-time incentives); company car tax, and circulation tax (i.e. recurring incentives). The value of the monetary incentive variable is then the sum of these six elements.

**Appendix B: Analysis of the impact of charging stations within a fixed-effects model**

For all FE models of Table 3 that include the variable for the level of charging stations two considerations can be made. First of all, the inclusion of charging stations *increases* the value of the monetary incentive estimate. This would be the case if in models 1-4 of Table 3 an omitted variable bias would be present. However, since charging stations, monetary incentive and EV registrations are all positively correlated (see page 12), one would expect the bias in models 1-4 to be positive, and not negative. Secondly, charging stations are statistically significant, but one would expect their estimates to be positive, and not negative.

Both elements are not in line with what expected, and suggest that the specifications of the model might not be correct. To understand what might be causing these results, I run different FE regressions on the full database, with and without the time trend. In all specifications, when the time trend is included the direction of charging stations changes and is not in line with what literature would suggest. The same results are found when using other database specifications (lagged charging stations; lagged charging stations and additional controls), when using a log version of charging stations, and also when dividing the variable in its two components (fast chargers and slow chargers). Finally, the inclusion of time dummies, instead of a time trend, does not change the significance and direction of the variable.

As all models which include a trend present significant but negative estimates of charging stations, the results suggest that the time specifications of the static linear model might be obscuring the expected impact of charging stations.

## Appendix B Table 1: Analysis of charging stations in a FE model

| VARIABLES | (1)<br>Charging model<br>log_evshare | (2)<br>Charging model with trend<br>log_evshare | (3)<br>Lagged charging model<br>log_evshare | (4)<br>Lagged charging model with trend<br>log_evshare | (5)<br>Full controls model<br>log_evshare | (6)<br>Full controls model with trend<br>log_evshare |
|---|---|---|---|---|---|---|
| charging | 0.136*** | -0.036*** | | | | |
| | (0.030) | (0.009) | | | | |
| L.charging | | | 0.123*** | -0.050*** | 0.049* | -0.062*** |
| | | | (0.033) | (0.014) | (0.028) | (0.013) |
| monetaryincentive | | | | | 0.270*** | 0.126** |
| | | | | | (0.063) | (0.053) |
| log_elecdieselratio | | | | | 4.692*** | -0.225 |
| | | | | | (1.047) | (0.890) |
| Trend | | 1,242.627*** | | 1,109.961*** | | 1,068.934*** |
| | | (60.619) | | (85.501) | | (105.215) |
| Constant | -6.418*** | -9,460.052*** | -5.935*** | -8,450.593*** | 2.407 | -8,139.521*** |
| | (0.073) | (461.178) | (0.065) | (650.499) | (2.278) | (801.262) |
| Observations | 310 | 310 | 279 | 279 | 279 | 279 |
| R-squared | 0.111 | 0.810 | 0.085 | 0.756 | 0.336 | 0.780 |
| Number of countryid | 31 | 31 | 31 | 31 | 31 | 31 |
| Adjusted R-squared | 0.777 | 0.777 | 0.777 | 0.777 | 0.777 | 0.777 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1